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Assessment of rainfall and NDVI anomalies in semi-arid regions using distributed lag models

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ABSTRACT

The semiarid regions of Ethiopia are exposed to anthropogenic and natural calamities. In this study, we assessed the relationship between Tropical Applications of Meteorology using Satellite data (TAMSAT) and MODIS Normalized Difference Vegetation Index (NDVI) data for the period 2000 to 2014 on decadal and annual basis using multivariate distributed lag (DL) models. Decadal growing season (June to September) values for kaftahumera were calculated from MODIS NDVI data. The growing season NDVI values are highly correlated with the precipitations during the whole study period. A lag of up to 30 days observed in most parts of our study region in which the rainfall has effects on vegetation growth after 40 days. The lag-time effects vary with the distribution of land use types and seasons. A lower correlation was observed in the woodland regions where significant deforestation occurred due to expansion of croplands. The loss in vegetation contributed to the low biomass production attributable to extended loss in vegetation cover.

Keywords: eMODIS; TAMSAT; lag; biomass; distributed lag (DL) models

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1. INTRODUCTION

The availability and distribution of rainfall is among the determinant factors for plant productivity in the semi-arid region[1].In addition other factors like: temperature, evapotranspiration, soil properties could affect the growth of dryland vegetation [2]. Land use land cover (LULC) is other important component which affects the vegetation condition in the semiarid environments. Population growth and excessive rate of natural resource consumption has threatened the world for complex environmental degradation [3]. It is common to see loss in vegetation cover resulted from over utilization of trees, conversion to cropland, grazing expansion and fire [4,5]. The loss in vegetation is contributing for the release of CO_2 that can be one of the greenhouse gas emitted to the current global warming [6,7].

Normalized Difference Vegetation Index (NDVI) has been a proxy for assessing vegetation productivity[8]. NDVI is strongly dependent on climatic variables for both temporal and spatial patterns [9]. Temporal NDVI analysis with high values of NDVI indicate a vigorousity of vegetation in a given region while lower NDVI values are indicators of vegetation degradation over time. Different studies also showed the strong relationship between NDVI and climate variables that can benefit for modeling crop yield and primary productivity in semi-arid regions [10,11]. In addition, the assessment and identification of climate variability is vital for differentiating environmental changes that can be either human induced or climate change [12].

The northwestern drylands of Ethiopia are currently facing deforestation and degradation due to excessive wood harvest, cropland expansion, fire, overgrazing and other related pressures of population growth [4,13,14]. On the otherhand there are some global studies which indicated variation in rainfall distribution across the east African regions[15]. However there is no assessment in evaluating the degree of loss in biomass accumulation and its relation to climatic variables and NDVI over the region. In this study, relationship between rainfall and NDVI lags established for quantitatively estimating the temporal changes in vegetation productivity over Kaftahumera.

2. MATERIALS AND METHODS

2.1. Study area

Kaftahumera is among the semiarid districts of northwestern Ethiopia situated between 13° 40′N and 14° 28′ N latitude and 36° 27′ E and 37° 32′ E longitude with altitude varying from 537 m to 1865 m above sea level (Fig. 1) and covering an area of about 6200 km^2. It is bordering the Sudano-Sahelian region which is known for its erratic rainfall, heavy dust storm movements and recurrent drought[16–18]. Rainfall in kafthumera is characterized as mono-modal pattern concentrated in only certain months of the year mainly from June to September (Fig.2). The mean annual rainfall ranges from about 450 mm to around 1000 mm. The mean maximum monthly temperature ranges between 33 °C to 42 °C. The vegetation of kaftahumera is mainly comprised of Acacia-Commiphora and Combretum-Terminalia woodlands[19].

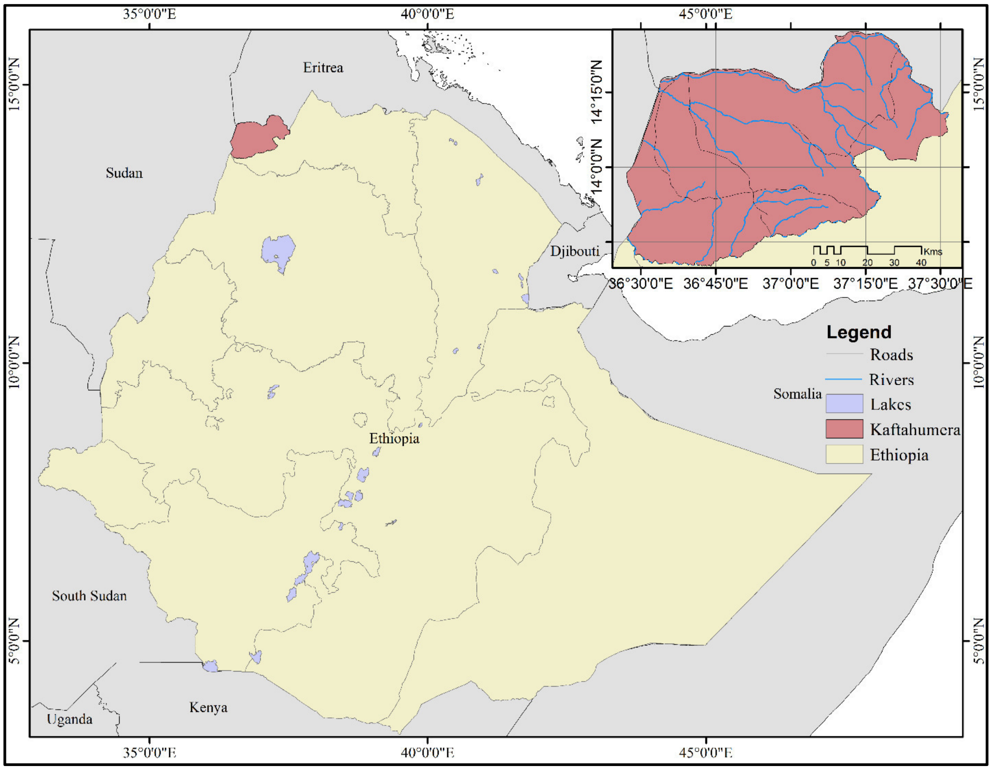

Figure 1. Geographic location of the study area.

2.2 Data

2.2.1. NDVI

We used the eMODIS NDVI data which is a product of the Moderate Resolution Imaging Spectroradiometer(MODIS) data acquired by the National Aeronautics and Space Administration's (NASA) Earth Observing System (EOS)[20]. The current eMODIS Africa data is produced in dekadal composites pentadally resulting in 72 composites per year[20]. The eMODIS Africa is a 10-day NDVI at 250 m resolution with geographic map projection and GeoTIFF format [20]. NDVI quantify the density of chlorophyll contained in vegetative cover and is defined as (NIR - RED) / (NIR + RED), where NIR is the near-infrared reflectance and RED is the visible-red reflectance [21].

The NDVI data are provided with quality raster rating the quality of each pixel with in the scene. We used the quality images to weight bad quality pixels in order to have low weight during raw image pre-processing. During the filtering process, the low weighted pixels are less considered for the construction of the new raster image. The stacked raster data then filtered using the Savitzky-Golay smoothing filters adjusting the filtering parameters in R statistical software[22].

2.2.2. Rainfall data

In this study we used Tropical Applications of Meteorology using Satellite data (TAMSAT) from 2000 to 2014 for a precipitation dataset. TAMSAT uses satellite imagery calibrated against historical ground based observations for estimating rainfall at a spatial resolution of about 4 km for the whole of Africa[23]. Meteosat thermal infrared (TIR) imagery were used for producing a 10-day rainfall estimates [23,24]. The TAMSAT precipitation dataset were assessed over Ethiopia considering gauge measurements and have shown the best agreement with the gauge measurments [25].

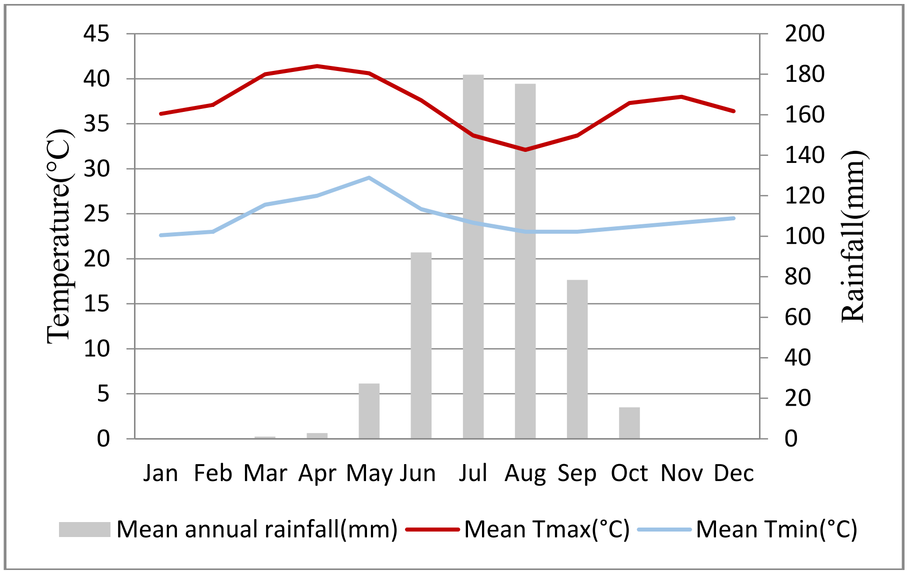

Figure 2 Climate graph of Kaftahumera

2.3 Method

The distribution of rainfall across semiarid of Kaftahumer is erratic and not follow a normal distribution across the measurement periods. The NDVI also shows deviation based on the vegetation productivity and availability of moisture for vegetation growth.On the other hand, there is an autocorrelation between the measurements of NDVI and rainfall across the years which affects the basic assumption of independence in regression analysis[26].

The seasonal variations in both NDVI and rainfall should be removed in order to discriminate the long term trend in NDVI and rainfall. The dataset were standardized so as to have standardized anomalies removing the seasonality as:

$$Z = (x - \mu)/\sigma \quad (1)$$

where x is the filtered data value of each month, μ is the monthly long term average and σ is the monthly standard deviation.

In this study, distributed Lag model (DL) is used for assessing the trend in the anomaly of climate variables and NDVI in order to evaluate the trends in vegetation productivity over Kaftahumera. DL is a distinct kind of a regression model that accounts for the lagged time responses between the input variables (Dominic, et al., 2002). This method was used to investigate the relationship between rainfall and NDVI in east Africa[26] considering the non-stationarity of NDVI and rainfall.

A regression analysis using DL models was made between the NDVI and rainfall anomalies after removing the trends and seasonal variation. DL regression analysis accounts for the lagged effects of explanatory variable on the response variable and takes the form :

$$Y_t=a+b_0x_t+b_1x_{t-1}+b_2x_{t-2}+\dots\dots e_t \quad (2)$$

where vector b is weight of each x series and e is the model residual.

Accordingly, we adopted the formula assigning rainfall as the explanatory variable and NDVI as the response variable as:

$$\mathrm{NDVI}_t = a + \sum_{i=0}^{i=max} b_j \, \mathrm{rainfall}_{t-j+e_j}$$

where bj is the impulse response weight vectors describing the weights assigned to current and past rainfall, a is the constant term and e isthe model residual

The maximum lag is fixed to 8 and a continuous fit made starting from a model containing zero as first order lag [27]. The optimal lags between rainfall and NDVI determined when the t statistics is significant and its p value is lessthan 0.05.

3. RESULTS

3.1 Mean NDVI

The distribution of mean long term NDVI and mean annual rainfall varies spatially according to the land use history (Fig.1). The southern and southeastern part of Kafthumera has higher mean rainfall amount compared to other parts of the study area. However the western,central and some eastern part which is mostly dominated by the human activities have lower mean NDVI. Areas which were once covered with woodlands located on the central and northwestern of Kaftahumera, has lower NDVI values which resulted from expansion of agricultural activities and human pressures. A higher correlation found between the mean NDVI and mean rainfall across the study area. Nevertheless the spatial variation in mean rainfall is not significant at $p< 0.1$.

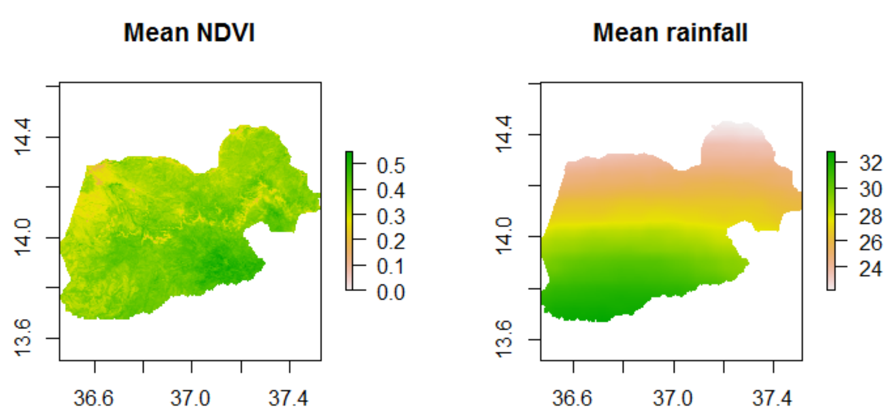

Figure 3.Mean NDVI and mean annual rainfall distribution of Kaftahumera

3.2 NDVI and rainfall correlation

In order to discriminate the significant lags that affected the relationship between NDVI and rainfall , a scatter plot made using the past lags of rainfall from current to 8 lags (one lag is 10 days using the eMODIS data and decadal TAMSAT rainfall data). The correlation values between the two datasets ranges between 0.53 to 0.89 (Fig.4) The lag test per each pixel also tested and the value ranges between 0.43 to 0.90 (not shown here). The correlation between the two datasets from lag_{t-2} to lag_{t-5} has shown positive and strong correlations where us other lags have positive correlation but more with more scatter relationships.

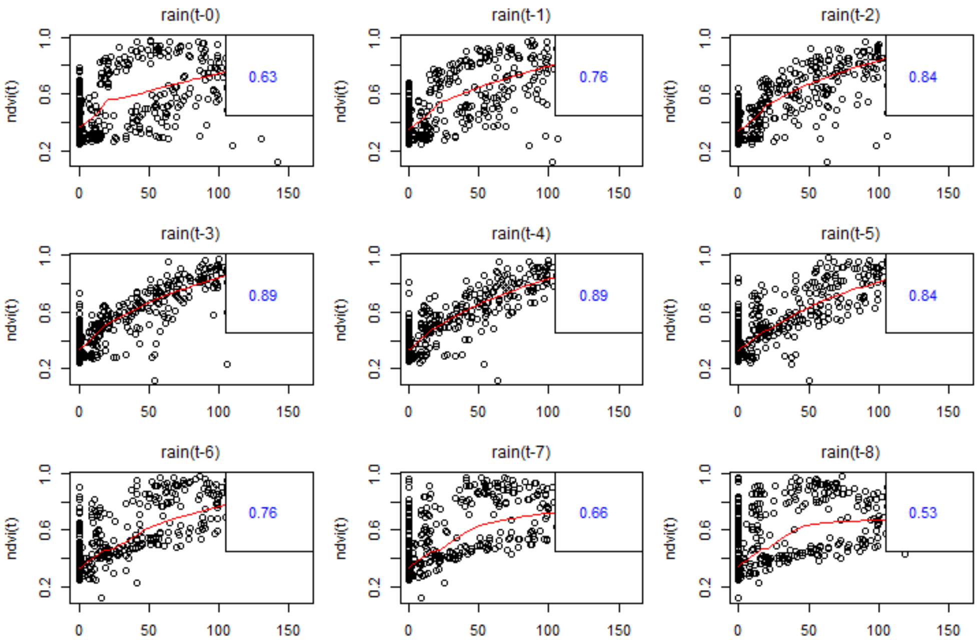

Figure 4. Scatter plots of NDVI and rainfall for different lags.

The spatial relationship between NDVI and rainfall displays a high spatial non-stationary (Fig.5). The spatial patterns of the relationship follow the patterns of distribution of vegetation and land cover types. There is a higher coefficient of determination (R^2) between rainfall and NDVI in areas covered with woody vegetations.

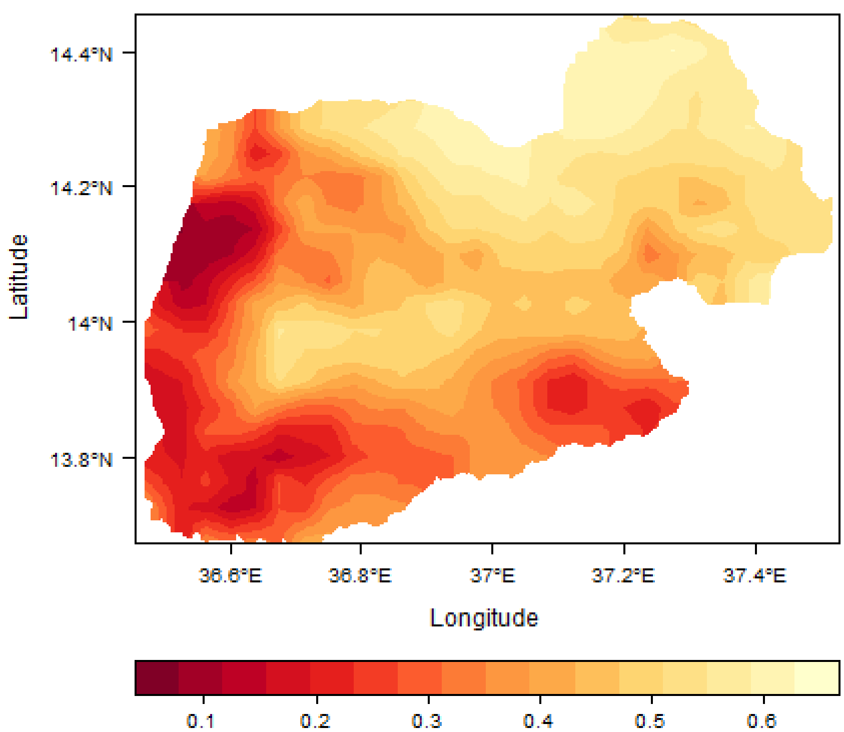

Figure 5. Spatial correlation between NDVI and rainfall of Kafthumera.

3.3. Lag identification and correlation

During regression analysis of time series NDVI and rainfall variables, we observed time series structures for the residuals of both data sets. This violates our assumption of error independence in the ordinary least squares regression. The violation of error independence results in wrong estimation of the coefficients and their standard errors; and should be adjusted fitting an autoregressive model.

The cross correlation function and the scatter plot are crucial for determining for identifying lags of the rainfall variable that can be used as predictors of the NDVI. Accordingly a multiple regression analysis was made between the NDVI and rainfall of past lags 2 to 6. The most dominant cross correlations between NDVI and rainfall occurred in lags of up to 8 (in 10 day scale). However the correlation test of the lag distribution is significant only upto lag 4 indication the rainfall effect on vegetation productivity is after about 40 days.

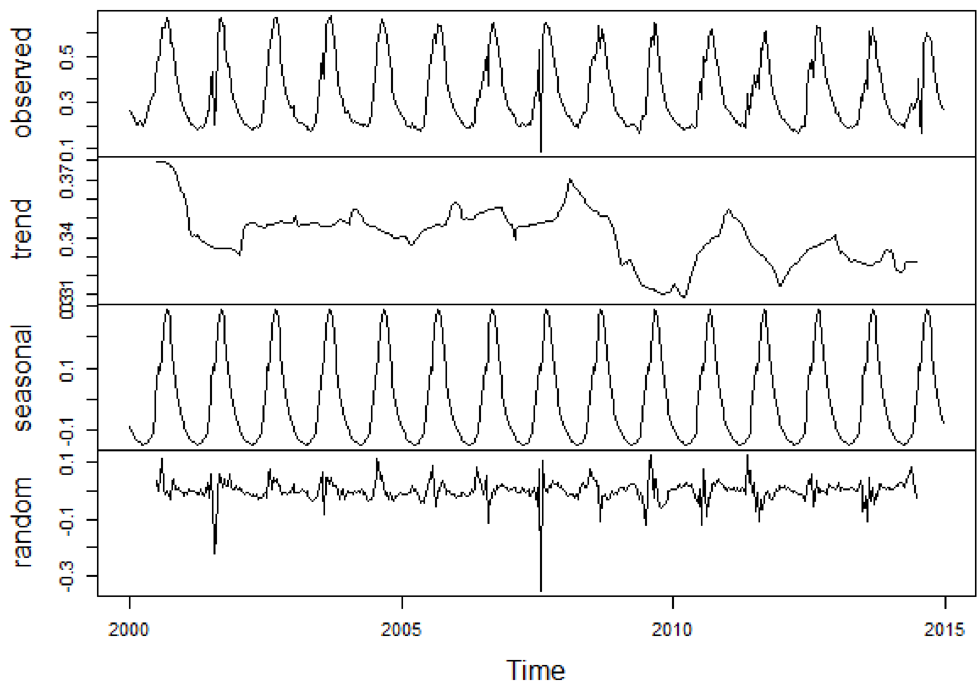

Figure 6. Decomposition of NDVI (sample plot from areas converted to cropland) into seasonal, trend and noise.

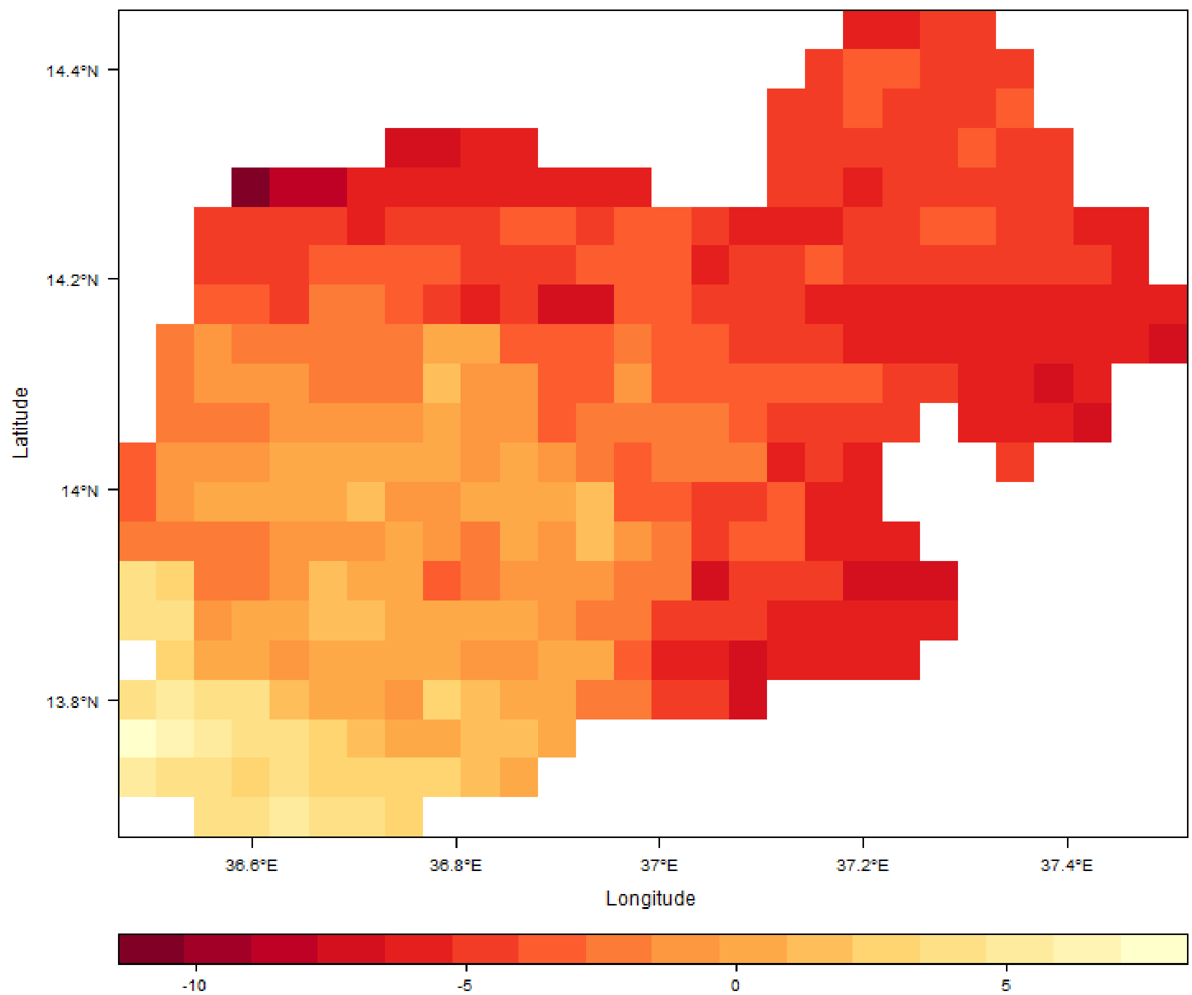

Figure 7.Spatial distribution of rainfall anomaly over kaftahumera

In figure 7 we analysed the spatial distribution of anomaly for the period 2000 – 2014. In the spatial feature distribution, more rainfall is observed on the southern part of Kaftahumera. This part of our study area also showed higher positive anomaly. However the anomaly is not significant across the whole region.

4.CONCLUSIONS

A lag regression between eMODIS NDVI and rainfall was made for the period 2000 to 2014 using DL models. The autocorrelation of the two datasets removed before testing for lag correlation. A 40 days maximu lag observed between the predictor (rainfall) and the response (NDVI) suggesting rainfall has effects on vegetation productivity after about fourty days. There is higher siginificant correlations between NDVI and rainfall across the study area. However there is no significant spatial correlation of rainfall over our study site.

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